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Electroencephalogram classification methods

***Abstract**. Today still big challenge in world to find efficient technique for perform recognition on mental tasks, and distinguish between them. This allow us to use Brain Computer Interface applications to helps disabled people to interaction with environment and control on external devices.*

***Streszczenie.** Obecnie duze znacznie ma rozpoznawanie aktywności umysłowej dzięki analizie aktywności mózgu. W artykule omówiono interfejs komputer-mózg. (**Metody klasyfikacji elektroencefalogramu**)*

Keywords: EEG, Lempel–Ziv Complexity, Turtle Graphics, EEG Data Similarity.
Słowa kluczowe: EEG, analiza danych, interfejs komputer-mózg.

Introduction

Today still big challenge in world to find efficient technique for recognition between mental tasks, and distinguish between them. This allow us to use Brain Computer Interface applications to helps disabled people to interaction with environment and control on external devices.

Electroencephalogram (EEG) represents complex irregular signals that may provide information about underlying neural activities in the brain [1]. The electrical nature of the human nervous system known as that variation of the surface potential distribution on the scalp that reflects functional activities emerging from the underlying brain [2]. This electrical surface potential variation can be recorded by affixing set of electrodes on the scalp, and measuring the signal between pairs of these electrodes after that filtered, amplified, and recorded these signals. The resulting data are called the Electroencephalograph (EEG) [2].

Source of EEG Generating

The EEG signals define as measurements of the currents when flowing during synaptic excitations of the dendrites of multiple pyramidal neuro cells in the cerebral cortex. When brain cells are activated, the synaptic currents are produced within the dendrites. Normally this current producing a magnetic field can be measurable by electromyogram (EMG) machines and an electrical field over the scalp measurable by EEG systems. Basically the current in each neuron cell of brain, is produced from pumping the positive ions of calcium, sodium, and potassium, and negative ions of chlorine, through the neuron membranes in the direction governed by the membrane potential, as structure of neuro cell in figure (1) [3].

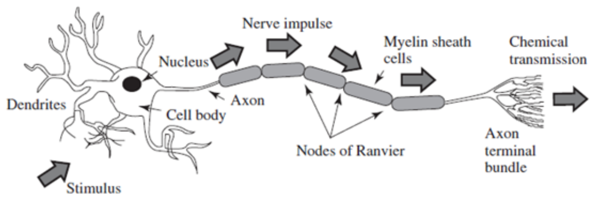

Fig. 1 Structure of Neuro Cell [3]

Non-negative Matrix Factorization

Non-negative Matrix Factorization (NMF) is an emerging method with a wide spectrum of applications, such as in data analysis, spectrumtry, language modelling, signal and image processing, and neurophysiology [4]. It aims to find two non-negative matrices whose product can well approximate the original matrix, which naturally leads to parts-based representation.

The standard definition for non-negative matrix factorization (NMF) of the matrix A as equation (1)

$$A = WH \tag{1}$$

where A is $m\,x\,n$, W is $m\,x\,r$, H is $r\,x\,n$, and $r < m$. Both W and H must contain only non-negative entries [5]. W is basis matrix, each column of which is basis vector, H is coefficient matrix, each column of which is new feature vector. That leads to dimensional reduction by choose the $r < m$ although it is open problem to decide the optimal r [6].

EEG classification by NMF

EEG signal classification or mental task recognition introduced by several researchers using various methods for analysis complex EEG data raw to understanding this complex data. Such as. Liu et al. have used Keirn and Aunon EEG data, and applied NMF to decomposition magnitude spectra of the EEG signal. Their result reached to 98%, and 82% when training and testing data from the same day, and different days respectively [6]. Rutkowski, et al. they have applied the combining a time-frequency representation of EEG signal with NMF. The proposed method is applying analysis in the time-frequency domain using empirical mode decomposition (EMD) method, then applying NMF to extract hidden non-negative factors, the purpose of this method is EEG features extraction and EEG patterns analysis [4]. Hyekyoung Lee et al. have proposed a method of feature extraction for motor imagery single trial EEG classification, they have applied NMF to select discriminative features in the time-frequency representation of EEG. This method structure of wavelet transform pre-processing, feature extraction based on NMF, and classification based on probabilistic model, this paper confirmed that the data selection scheme improved the classification accuracy by 2.14% and the mutual information by 0.1127 bit [7]. Hyekyoung Lee et al. they have extension their previous work on the use of NMF for EEG classification to using Nonnegative Tensor Factorization (NTF) for determine discriminative spectral features and use the Viterbi algorithm to continuously classify multiple mental tasks. They conclude to NTF can find the hidden structures for new dimension such as time or class. Continuous EEG classification can reduce the restriction of EEG experiment since it doesn't need the trial structure [8]. Liu Mingyu et al. they have applied NMF for EEG signal processing, to investigate an efficient model for the features extraction and classification of EEG signal during different attention-level mental tasks. They conclude that NMF lead more localized and sparse features than power spectrum method and principal component analysis. It was found that the NMF algorithm performs better than other two methods, and suitable for EEG signal feature extraction [9]. Hyekyoung Lee and Seungjin Choi, have presented methods of learning discriminative spectral features from large data matrix involving EEG power spectrum because the size of a data matrix grows, by Incorporating CUR decomposition with NMF that led to downsize the large data matrix such that NMF could be applied to compute discriminative spectral features. Their Experimental results with two EEG data sets in BCI competition, confirm the useful behavior of the proposed method [10]. Hyekyoung Lee et al. they have applied Kernel NMF to extract discriminative spectral features from the time-frequency representation of EEG data, their method was successful for apply KNMF to task of learning discriminative spectral feature from EEG data for classification, the experiments on two benchmark EEG datasets confirmed the performance gain over standard NMF [11].

Hyekyoung Lee, and Seungjin Choi, have presented Group NMF (GNMF) for analyze EEG data of multiple subjects. They have compared GNMF with NMF and some modified NMFs, in the task of learning spectral features from EEG data, the experiments on brain computer interface (BCI) competition data indicate that GNMF improves the EEG classification performance [12]. Phan and Cichocki, they have proposed a new fast non-negative tensor factorization (NTF) algorithm which factorizes the approximate tensor obtained from the Parallel factor analysis (PARAFAC). The proposed algorithm have been high performance that confirmed even for noisy data, and the large scale EEG benchmark, it is fast comparing with other existing NTF algorithms [13].

Lee et al. they have presented a semi-supervised version of NMF (SSNMF) which jointly exploited both (partial) labeled and unlabeled data to extract more discriminative features than the standard NMF. Their experiments on EEG datasets in BCI competition confirm that SSNMF improves clustering as well as classification performance, compared to the standard NMF [14]. Shin et al. have proposed new method generative model of a group EEG analysis, based on appropriate kernel assumptions on EEG data. Their proposed models find common patterns for a specific task class across all subjects as well as individual patterns that capture intra-subject variability. The validity of the proposed method have been tested on the BCI competition EEG dataset [15].

Dohnalek et al. have proposed method for signal pattern matching based on NMF, also they used short-time Fourier transform to preprocess EEG data and Cosine Similarity Measure to perform query-based classification. This method of creating a BCI capable of real-time pattern recognition in brainwaves using a low cost hardware, with very cost efficient way of solving the problem [16].

EEG and Lempel-Ziv complexity

Abasolo et al. have investigated the EEG background activity in patients with Alzheimer's disease using non-linear analysis methods – Lempel-Ziv (LZ) complexity and computation of the central tendency measure (CTM) of the EEG [17].

The Lempel–Ziv (LZ) complexity for sequences of finite length was suggested by Lempel and Ziv [18]. It is a nonparametric, simple-to-calculate measure of complexity in a one-dimensional signal that does not require long data segments to compute [19]. LZ complexity is related to the number of distinct substrings and the rate of their recurrence along the given sequence [20], with larger values corresponding to more complexity in the data. It has been applied to study the brain function [21], brain information transmission [22] and to detect ventricular tachycardia and fibrillation [19]. Preliminary evidence suggests that, applied to EEGs, LZ complexity is predictive of epileptic seizures [20] and can be useful to quantify the depth of anaesthesia [23,24]. Moreover, it has been applied to extract complexity from mutual information time series of EEGs in order to predict response during isoflurane anaesthesia with artificial neural networks [25].

LZ complexity analysis is based on a coarse-graining of the measurements, so before calculating the complexity measure $c(n)$, the signal must be transformed into a finite symbol sequence. In this study we have used following sequence conversion methods:

1. 0-1sequence conversion

The median value is estimated as a threshold T_d. By comparison measured signal data value with T_d, the signal data are converted into a 0-1 sequence $P = s(1), s(2), s(3), s(4), \dots, s(n)$, where n is length of signal data sequence and defined $s(i)$ by formula (2):

$$s(i) = \begin{cases} 0 \text{ if } x(i) < T_d \\ 1 \text{ if } x(i) \le T_d \end{cases} \tag{2}$$

2. 0-1-2 sequence conversion

For each EEG segment, the median x_m, maximum x_{max} and minimum x_{min} are calculated. After calculation the maximum, minimum and median value we set two threshold values. $T_{d1} = x_m - |x_{min}|/16$ and $T_{d2} = x_m + |x_{min}|/16$. Then the EEG data converted into a 0-1-2 sequence $P = s(1)$, $s(2), s(3), s(4), \dots, s(n)$, with $s(i)$ defined in following formula (3):

$$s(i) = \begin{cases} 0 \text{ if } x(i) < T_{d1} \\ 1 \text{ if } x(i) < T_{d2} \\ 2 \text{ if } x(i) \ge T_{d2} \end{cases} \tag{3}$$

The sequence P is scanned from left to right and the complexity counter $c(n)$ is increased by one unit every time a new subsequence of consecutive characters is encountered. The complexity measure can be estimated using algorithm [19,23,24]:

1. Let S and Q denote two subsequences of P and SQ be the concatenation of S and Q, while sequence $SQ\pi$ is derived from SQ after its last character is deleted (π means the operation to delete the last character in the sequence). Let $v(SQ\pi)$ denote the vocabulary of all different subsequences of $SQ\pi$. At the beginning, $c(n) = 1$, $S = s(1)$, $Q = s(2)$, therefore, $SQ\pi = s(1)$.
2. In general, $S = s(1)$, $s(2)$, …, $s(r)$, $Q = s(r + 1)$, then $SQ\pi = s(1), s(2), \dots, s(r)$; if Q belongs to $v(SQ\pi)$, then Q is a subsequence of $SQ\pi$, not a new sequence.
3. Renew Q to be $s(r + 1)$, $s(r + 2)$ and judge if Q belongs to $v(SQ\pi)$ or not.
4. Repeat the previous steps until Q does not belong to $v(SQ\pi)$. Now $Q = s(r + 1)$, $s(r + 2)$, …, $s(r + i)$ is not a subsequence of $SQ\pi = s(1)$, $s(2)$, …, $s(r + i - 1)$, so increase $c(n)$ by one.
5. Thereafter, S is renewed to be $S = s(1)$, $s(2)$, …, $s(r + i)$, and $Q = s(r + i + 1)$.

These procedures have to be repeated until Q is the last character. At this time the number of different subsequences in P – the measure of complexity – is $c(n)$.

In order to obtain a complexity measure $c(n)$ which is independent of the sequence length. $c(n)$ should be normalized. If the length of the sequence is n and the number of different symbols in the symbol set is α, it has been proved [18] that the upper bound of $c(n)$ is defined in [18].

In general, $n/\log(n)$ is the upper bound of $c(n)$, where the base of the logarithm is α,

(4) $$\lim_{n\to\infty} c(n) = b(n) = \frac{n}{log_{\alpha}(\mathrm{n})}$$

and $c(n)$ can be normalized via $b(n)$:

(5) $$C(n) = \frac{c(n)}{b(n)}$$

$C(n)$, the normalized LZ complexity, reflects arising rate of new patterns along with the sequence. Thus, it captures the temporal structure of the sequence [17,18].

EEG, Turtle Graphics Commands and Lempel-Ziv complexity

In our experiment we used a different EEG data conversion method. We converted EEG data segments with turtle graphic into commands [26,27] represented by a single character. Each character present one direction angle of EEG data curve, created from measured data (Fig. 2). This angle is calculated between two values.

In our experiment we do not deal with $c(n)$ measure of the complexity. From the individual EEG data sequences after conversion we create a list of LZ subsequences. One subsequence list is created for each data segment.

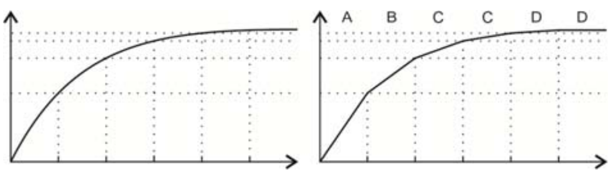

Fig. 2 Data conversion [28]

The comparison of the LZ sequence lists is the main task. The lists are compared to each other. The main property for comparison is the number of common sequences in both compared lists. This number is represented by the sc parameter in the following formula (6), which is a metric of similarity between two turtle commands lists after using LZ complexity.

(6) $$SM = \frac{sc}{\min(c_1, c_2)}$$

Where: sc - count of common LZ sequences in both sequence segments, c_1, c_2 - count of LZ sequences in first second segment.

The SM value is in the interval between 0 and 1. If $SM = 1$, then the documents are equal, have many common LZ sequences, and they have the highest difference when the result value of $SM = 0$, they have a few common LZ sequences [28].

Experiment Results

We made similarity between the EEG trials for left hand back movement and imaging left hand back movement task. Our results are listing in the Table 1, the maximum similarity results of mental tasks by our method reach to 100.00%, minimum similarity was 30.00% and average value of similarity was 52.36%. Our model reached accuracy up to 52.63%.

Table 1. Similarity results.

	Minimum	Maximum	Average
Correctly identified	30.00%	100.00%	52.63%
Incorrectly identified	0.00%	70.00%	47.37%
True positive rate	0.00%	100.0%	35.53%
False positive rate	0.00%	100.0%	55.26%
Accuracy	30.00%	100.00%	52.63%

On Figure 3 we can see accuracy for sensor. The most accuracy values are between 40% and 60%.

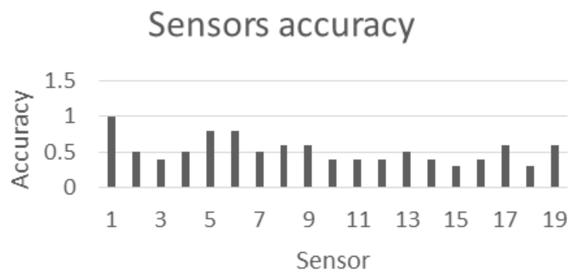

Fig. 3 Sensors accuracy

Conclusion

We made our experiments on EEG signals from one subject performing left hand back movement task in three trials, and other trial for imaging left hand back movement, we applied FFT to EEG data, removing high frequencies, applied Invers FFT, represent EEG data by turtles graphics, then finding the maximum similarity between these trials by LZ compression. The experiment results on EEG data showed the maximum similarity results of mental tasks by our method reach to 100%, minimum similarity was 30.00% and average value of similarity was 52.36%. Our model reached accuracy up to 52.63%. In future work we will try to collect EEG data using Emotiv EEG neuro headset, and use this data to find similarity between mental tasks by our proposed method to analysis and recognition on mental tasks.

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REFERENCES

[1] Bhattacharya J., Petsche H., *Universality in the brain while listening to music*, Proc. the Royal Society Lond. B., 2001, No. 268, 2423-2433

[2] Ochoa J. B., Molina G. G., Ebrahimi T., *EEG Signal Classification for Brain Computer Interface Applications*, Ecole Polytechnique Federale De Lausanne, 2002

[3] Sanei S., Chambers J. A., *EEG Signal Processing*, 2007, John Wiley & Sons Ltd, The Atrium, Southern Gate, Chichester, West Sussex PO19 8SQ, England

[4] Rutkowski T. M., Zdunek R., Cichocki A., *Multichannel EEG brain activity pattern analysis in time-frequency domain with nonnegative matrix factorization support*, International Congress Series, 2007, No. 1301, 266-269

[5] David Skillicorn., *Understanding Complex Datasets*. 2007 by Taylor and Francis Group, LLC

[6] Weixiang L., Nanning Z., and Xi L., *Nonnegative Matrix Factorization for EEG Signal Classification*, Advances in Neural Networks - ISNN 2004, International Symposium on Neural Networks, Dalian, China, 2004, 470 – 475

[7] Lee H., Cichocki A., Choi S., *Nonnegative Matrix Factorization for Motor Imagery EEG Classification*, Artificial Neural Networks - ICANN 2006 16th International Conference, Athens, Greece, September 10-14, 2006, 250-259

[8] Lee H., Kim Y., Cichocki A., Choi 6S., *Nonnegative Tensor Factorization for Continuous EEG Classification*, International Journal of Neural Systems, Vol. 17, No. 4 (2007), 305-317

[9] Mingyu L., Hongbing J., Chunhong Z., *Non negative Matrix Factorization and Its Application in EEG Signal Processing*, Bioinformatics and Biomedical Engineering The 2nd International Conference, Xian, 2008, 2146-2148

[10] Lee H., Choi S., *CUR+NMF for Learning Spectral Features from Large Data Matrix*, Neural Networks, 2008. IJCNN 2008. (IEEE World Congress on Computational Intelligence). IEEE International Joint Conference, Pohang, 1592-1597

[11] Lee H., Cichocki A., Choi S., *Kernel nonnegative matrix factorization for spectral EEG feature extraction*, 2009, 3182-3190

[12] Lee H., Choi S., *Group Nonnegative Matrix Factorization for EEG Classification*,12th International conference on Artificial and Statistics (AISTATS), Florida, 2009, 320-327

[13] Phan A. H., Cichocki A., *Fast Nonnegative Tensor Factorization for Very Large-Scale Problems Using Two-Stage Procedure*, Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP), 2009 3rd IEEE International Workshop, 297-300

[14] Lee H., Yoo J., Choi S., *Semi-Supervised Nonnegative Matrix Factorization*, Signal Processing Letters, IEEE, 2010, 4-7

[15] Shin B., Oh A., *Bayesian Group Nonnegative Matrix Factorization for EEG Analysis*, CoRR dec 2012

[16] Dohnalek p., Gajdos p., Peterek t., Penhaker M., *Pattern Recognition in EEG Cognitive Signals Accelerated by GPU*, International Joint Conference CISIS'12-ICEUTE'12-SOCO'12 Special Sessions Advances in Intelligent Systems and Computing Volume 189, 2013, 477–485

[17] Abásolo D., Hornero, R., Gómez, C., García, M., López, M., *Analysis of EEG background activity in Alzheimer's disease patients with Lempel-Ziv complexity and central tendency measure*, Medical Engineering and Physics 28 (4) , 2006, 315-322

[18] Lempel A., Ziv J., *On the complexity of finite sequences*, IEEE TransInform Theory 1976, No. 22, 75–81

[19] Zhang X. S., Zhu Y.S., Thakor N.V., Wang Z.Z., *Detecting ventricular tachycardia and fibrillation by complexity measure*, IEEE Trans Biomed Eng 1999, No. 46, 548–55

[20] Radhakrishnan N., Gangadhar B. N., *Estimating regularity in epileptic seizure time-series data. A complexity-measure approach*, IEEE Eng Med Biol 1998, No. 17, 89–94

[21] Wu X., Xu J., *Complexity and brain functions*, Acta Biophys Sinica 1991, No. 7, 103–106

[22] Xu J., Liu Z. R., Liu R., Yang Q. F., *Information transformation in human cerebral cortex*, Physica D 1997, No. 106, 363–74

[23] Zhang X. S., Roy R. J., Jensen E. W., *EEG complexity as a measure of depth of anesthesia for patients*, IEEE Trans Biomed Eng 2001, No. 48, 1424–33

[24] Zhang X. S., Roy R. J., *Derived fuzzy knowledge model for estimating the depth of anesthesia*, IEEE Trans Biomed Eng 2001, No. 48, 312–23

[25] Huang L., Yu P., Ju F., Cheng J., *Prediction of response to incision using the mutual information of electroencephalogram during anesthesia*, Med Eng Phys 2003, No. 25, 321–327

[26] Prusinkiewicz P., *Graphical applications of L-system*, Graphical Interface, 1986, 247- 253

[27] Goldman R., Schaefer S., Ju T., Turtle geometry in computer graphics and computer-aided design, 2004, 1471–1482

[28] Jahan I. S., Prilepok M., Snasel V., *EEG Data Similarity Using Lempel–Ziv Complexity*, unpublished

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